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A hybrid short-term traffic flow forecasting method based on spectral analysis and statistical volatility model

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ABSTRACT

Short-term traffic flow prediction is a critical aspect of Intelligent Transportation System. Timely and accurate traffic forecasting results are necessary inputs for advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS). Despite the proliferation of advanced methodologies, modeling the uncertainty of traffic conditions is still a challenge, especially during congested situations. This paper presents a hybrid model for multi-step ahead traffic flow forecasting in a freeway system with real-time traffic flow data. This proposed methodology forecasts traffic flow by decomposing the data into three modeling components: an intra-day or periodic trend by introducing the spectral analysis technique, a deterministic part modeled by the ARIMA model, and the volatility estimated by the GJR-GARCH model. The aim of this study is to provide deeper insights into underlining traffic patterns and to improve the prediction accuracy and reliability by modeling these patterns separately. The forecasting performance of the proposed hybrid model is investigated with real time freeway traffic flow data from Houston, Texas. The experimental results demonstrate that the proposed method is able to unearth the underlying periodic characteristics and volatility nature of traffic flow data and show promising abilities in improving the accuracy and reliability of freeway traffic flow forecasting in multi-step ahead forecasting.

1. Introduction

Short-term traffic flow prediction constitutes a fundamental input for Intelligent Transportation System (ITS), which improves transportation safety and mobility by applying advanced communications technologies in vehicles and into transportation infrastructures. The performance of ITS technologies largely depends on the quality and the accuracy of "real-time" traffic information. The accurate and timely traffic data not only allow travelers to make better-informed travel decisions, but also transform transportation management. Because of its importance, short-term predication of traffic flow has generated great interest among researchers and a significant number of methods exist in the literature. These existing methods include: spectral analysis method (Nicholson and Swann, 1974), regression method (Sun et al., 2003; Kamarianakisa et al., 2010), time series model (Voort van der et al., 1996; Ishak and Al-Deek, 2002; Mina and Wynterb, 2011), Kalman filtering methods (Iwao, 1984), support vector regression methods (Wu et al., 2004), neural network methods (Dougherty, 1995; Ledoux, 1997; Vlahogianni et al., 2005), chaotic theory (Hu et al., 2003), fuzzy logic system (Zhang and Ye, 2008; Dimitriou et al., 2008), wavelet network models (Xie and Zhang, 2006) and artificial intelligence (Huang and Sadek,

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2009). Reader interested in details of models that applied in traffic prediction field could refer to review papers such as Adeli (2001), Vlahogianni et al. (2004), Van Lint and Van Hinsbergen (2012).

Traffic flow prediction is a complex problem. Traffic flow not only exhibits periodic variations, some of which are obscured by noise, but also reveals stochastic behaviors affected by exogenous factors such as traffic incident, weather, and roadway conditions (Lan et al., 2008; Vlahogianni et al., 2006). Detecting the regular behaviors in traffic data masked by noise and extracting them from the data would improve our understanding of the system and make predictions more accurate. At the same time, because the sudden drops or increases of traffic flow are usually difficult to be captured by traditional forecasting methodologies, learning and modeling the stochastic traffic behaviors would also potentially improve forecasting accuracy. To statistically analyze the behaviors of traffic flow data, decomposition of the traffic flow data into different components and analyzing them with suitable methods may prove beneficial (Chan et al., 2012; Jiang and Adeli, 2004, 2005; Tchrakian et al., 2012).

From the perspective of the basic structure of the traffic stream (periodic trend), the popular and prevailing view in urban traffic-flow theory considers the traffic mostly periodic, over a 24-h period for weekdays, or over a week for both weekdays and weekends. Relatively speaking, periodicities in traffic-flow rates at various time intervals during the day are less addressed in transportation literature. To address these periodicities, the frequency domain approach—spectral analysis of such process—can be very informative. Different from time domain approaches that predict the present based on regressions over the past, frequency domain approaches are regressions on periodic sines and cosines. The frequency approach has proven effective at capturing intra-day periodicities. Dendrinos (1994) applied Fourier transform and spectral-density analysis to traffic flow data and demonstrated that smaller cycles exist besides the obvious 24-h cycle and the overlay of each of them produces the seemingly random traffic counts over the one-day period. Stathopoulos and Karlaftis (2001) used spectral analysis to reveal possible common cyclical components between two successive loop detectors. This common cyclical component may not be distinguishable in a time domain approach. Although, in literature, traffic flow forecasting methods mostly focused on the time domain approach, the frequency domain approach may give important insights into the basic structure of traffic data which is not apparent from the analysis in time domain.

While the frequency domain approach uncovers the cyclical traffic flow characteristics over time, the time domain approach reveals the correlations of traffic data at different time. In other words, the time domain approach considers the current value of traffic flow data as a function of its past values. As mentioned previously, the literature is rich with time domain approaches, such as the classical ARIMA, spatio-temporal autoregressive models, and state-space models. Among the time domain approaches, Autoregressive Moving Average (ARIMA) (Tsay, 2005) model is one of the most widely used regression techniques. Its applications in freeway traffic forecasting can be traced back to 1979 (Ahmed and Cook, 1979). Examples of ARIMA model applications in traffic forecasting range from univariate ARIMA model (Voort van der et al., 1996; Williams et al., 1998) to multivariate ARIMA model (Williams, 2001). Because of its well defined theoretical foundation and effectiveness in prediction (Karlaftis and Vlahogianni, 2009), the ARIMA model gradually has become a standard method to compare with newly developed forecasting models. Although these time domain models provide promising ability to forecast the expected value of traffic-flow, the inherent volatile nature of traffic data is still left unexplained.

Recently, transportation professionals began to make use of statistical volatility models in dealing with the uncertainty and variability in traffic system. This kind of methods can explain the inherent volatility with non-linear regression on historical traffic data and can provide Prediction Intervals (PIs) that are more accurate. Different from traditional methods that assume constant variance, the volatility models forecast time-dependent variances. The ARCH model, introduced by Engle (1982), relaxes the assumption of constant variance and assumes that the apparent changes in volatility of time series can be predictable. By providing some volatility measures, the ARCH model has the ability to measure the volatile nature of the data. Although the structure of the ARCH model is simple and easy to understand, many parameters are often required to describe the volatility process. Based on the theory of ARCH model, Bollerslev (1986) proposed a useful extension known as GARCH, allowing for a much more flexible lag structure. Existing studies demonstrated that traffic parameters display time-dependent volatilities for their variance part and applied the GARCH model in the traffic parameters' forecasting field (Kamarianakis et al., 2005; Yang et al., 2010). Driven by the successful implementation of standard GARCH models, some extensions of the GARCH model have also been proposed in modeling traffic volatilities (Karlaftis and Vlahogianni, 2009; Zhang et al., 2013). These studies indicated that the apparent changes in the volatility of traffic data are predictable and may result from a specific type of non-linear function.

Taking advantage of these unique properties in different models may lead to more efficient and reliable forecasting results. Thus, some recent studies proposed hybrid methods that are able to identify both the intra-day trend and non-reproducible flow patterns to improve the forecasting accuracy. Wei and Chen (2012) developed a hybrid EMD-BPN forecasting approach that combines empirical mode decomposition (EMD) and back-propagation neural networks (BPN) to predict short-term passenger flow in metro systems. They first decomposed passenger flow into a set of intrinsic mode function (IMF) components and identified the important ones as inputs for BPN passenger flow forecasting model. Wang and Shi (2013) proposed a traffic speed forecasting hybrid model(C-WSVM) using Support Vector Machine (SVM) regression theory. They proposed the C-WSVM model by using a wavelet function to construct the kernel function that can capture the non-stationary characteristics of the short-term traffic speed data, and by using the Phase Space Reconstruction theory to identify the input space dimension. Chen et al. (2012) compared different highway traffic prediction models' performance by using either original traffic data or residual data with the intra-day trend removed. Their test results indicated that the prediction